Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2013 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

6-18-2013

Price Elasticity in Electronic Markets: Evaluating Quality and Product Information for Search and Experience Products

Kyunghee Lee
Korea Advanced Institute of Science and Technology, nickend@business.kaist.ac.kr

Byungtae Lee
Korea Advanced Institute of Science and Technology, btlee@business.kaist.ac.kr

PRICE ELASTICITY IN ELECTRONIC MARKETS: EVALUATING QUALITY AND PRODUCT INFORMATION FOR SEARCH AND EXPERIENCE PRODUCTS

Kyunghee Lee, College of Business, Korea Advanced Institute of Science and Technology, Seoul, Korea, nickend@business.kaist.ac.kr

Byungtae Lee, College of Business, Korea Advanced Institute of Science and Technology, Seoul, Korea, btlee@business.kaist.ac.kr

Abstract

Evidence has shown that the provision of product information in electronic markets decreases the price elasticity of demand due to the 'fit' cost. This effect, however, could differ according to how consumers perceive the value of the product information to their quality evaluation procedures. If the information has very limited value, then they may not rely on it; thus, the demand elasticity may not decrease as predicted. The value of information to the quality evaluation procedure is determined by the consumer's difficulty in judging product quality. Specifically, product attributes related to the quality of experience products cannot be ascertained by prior search and the value of information in this case is therefore low. Based on this prediction, this research investigates how the price elasticity of demand differs in relation to the difficulty of evaluating quality and how it affects the influence of product information provided in electronic markets on elasticity. Groupon sales data are used to empirically test these questions. The findings confirmed that elasticity is lower for experience products than for search products. This also suggests that the provision of product information lowers elasticity in differentiated product markets and that its effect is stronger for search products than experience products.

Keywords: product information, search and experience products, fit cost, price elasticity of demand, Groupon, Social commerce

1 INTRODUCTION

As the Internet has rapidly changed the traditional retailing business, the features of online shopping that impact consumer demand elasticity have been discussed. In economy perspective, the frictionless markets and price elasticity hypothesis suggest that the ability to compare prices is extremely improved online, which increases price elasticity (Alba et al. 1997; Smith et al. 2001). In contrast, some researchers have focused on a different type of information provided online: product quality information. The online environment not only lowers the search cost of price comparison, but also lowers the search cost of product information related to quality, which makes consumers more aware of product quality, resulting in decreased price elasticity in differentiated product markets (Bakos 1997). Some studies contend that the latter effect outweighs the former because the cost of obtaining quality information is far higher than that of obtaining price information (Nelson 1970). Hence, the net effect of information provision in electronic markets may lead to decreased price elasticity (Granados et al. 2012; Lynch and Ariely 2000).

The effect of product information on elasticity, however, has been conceived somewhat as a generalized influence in the aforementioned studies. In fact, since product information is used to evaluate quality, it should be considered that the value that information brings to consumers' quality evaluation procedures could determine the extent to which they would respond to price levels.

Price elasticity decreases with product quality information because it substantially reduces quality uncertainty and reveals how 'fitted' the product is to customers (Bakos 1997). Thus, the degree of variation in elasticity can be determined by the marginal impact of information on the reduction of uncertainty. It is noteworthy that the extent to which uncertainty is mitigated by the provision of quality information is influenced by the inherent nature of the product itself. For example, some types of product information, such as relating to the specifications of hardware components, which can be easily searched for on the Internet, could be valued differently in the evaluation procedure according to the product type. If the product's quality cannot be assessed through *search* but only by *experience*, the impact of information obtained through search may be very limited. This type of product requires more valuable and costly information to be obtained for consumers to properly evaluate its quality. It can therefore be suspected that the importance of product information provided online may vary according to the difficulty involved in determining the quality of a product.

We focus on the impact of the difficulty of evaluating product quality on the price elasticity of demand. Along these lines, this research investigates the two following questions. First, how does the price elasticity of demand differ according to the difficulty of evaluating quality? Second, how does it affect the influence of the product information provided in electronics markets on the price elasticity of demand? This paper presents an empirical analysis on these questions using Groupon sales data.

Groupon is a social commerce site that sells highly discounted coupons for mostly local goods and services. Most products sold on Groupon are *experience* goods (services), such as spa and beauty salon services. In other words, Groupon is more of a differentiated products market rather than a commodities market. In addition, Groupon sells a wide range of product categories. Despite theoretical reasoning, previous studies have not been able to empirically test the aforementioned questions due to the limited variety of product categories in their data sets. Because Groupon data contain precise sales numbers across a wide range of product categories, it is possible to operationalize the difficulty of evaluating quality based on Nelson's classification of search and experience goods.

It is observed that the price elasticity of demand is higher for search products than for experience goods, and that price elasticity in electronics markets varies according to the extent to which it is difficult to evaluate product quality. In addition, it is understood that product quality information in electronics markets actually decreases price elasticity. This evidence supports the argument that in differentiated product markets, consumers become aware of which product is more fitted to their preferences by obtaining more information if the quality of the product is more likely to be verified through additional information available on the Internet. However, if the product does not belong to such category, additional information has no effect on price elasticity. This result has not been considered in the previous literature.

The remainder of this paper is organized as follows. We begin with hypothesis development, which provides the theoretical foundation of the study. In the next section, an empirical analysis is presented, describing the generation of the hypotheses, the empirical model specifications, methods for product categorization, and the employed data. Finally, we present our empirical results, followed by a discussion and implications.

2 HYPOTHESIS DEVELOPMENT

2.1 Quality Evaluation of Search and Experience Products

According to Nelson (Nelson 1970), the cost of obtaining quality information is much higher than that of obtaining price information. If the cost of the estimation procedures becomes sufficiently high, consumers will attempt to access information in different ways. A typical method of obtaining information about quality is through searching, in which consumers inspect a set of options prior to purchasing the product (Nelson 1970). For certain products or services, the consumer can discover their quality by directly experiencing them. Products associated with the former are called search goods and those associated with the latter are called experience goods.

Due to the differences in the cost of search between the two types of products, it is predicted that a larger sample size is expected for search products than experience products because a greater number of searches is possible with lower search cost. Because the elasticity of demand is a function of “the number of close substitutes which a consumer can compare,” the larger sample size for search products would lead to a higher price elasticity of demand and subsequently lower monopoly power (Nelson 1970).

This difference also leads to variations in the extent to which information is available for consumers in the estimation procedure. The high search costs of experience products limit the information available to consumers relative to search products, for which consumers can search for quality information without incurring substantial costs. Thus, for experience products, for which less information is available, consumer knowledge may be limited to the product’s price, in which case a generally positive relationship between price and quality must be assumed (Nelson 1970; Nelson 1975). Wolinsky (1983) also noted that prices may serve as quality signals that exactly differentiate levels of quality. This perceived positive relationship between price and quality therefore makes consumers less sensitive to price changes.

This statement has been intensively investigated in marketing research. Numerous studies on this relationship confirm that the price-quality relationship is relevant even if it cannot be proven that this relationship is universally persistent regardless of other factors (Gardner 1971; Monroe 1973; Olson 1976; Rao and Monroe 1989). One very important feature that influences this effect is the existence of other sources of information (Chang and Wildt 1994; Dodds et al. 1991; Monroe 1973; Rao and Monroe 1988; Rao and Monroe 1989). In many studies, it has been shown that multiple cues weaken the price-quality relationship because the presence of other information may decrease the importance of price in the evaluation process. In other words, other information makes the price level less useful as a signal of quality. Because the search cost of search products is far lower than that of experience products, it would be much easier to find alternative sources of product information for search products; thus, for experience products, for which high search costs restrict information availability, the price-quality relationship is stronger than for search products. A positive price-quality relationship clearly decreases price elasticity as price sensitivity (dQ/dP) decreases. Thus, variations in price elasticity by product types can be predicted as follows.

Hypothesis 1: Price elasticity is higher for search products than experience products.

2.2 Product Information in Differentiated Markets

Stigler (1961) presents how demand becomes less elastic due to lack of information: This occurs because limited information leads to a smaller sample size of products, leaving consumers with few options to choose from such that they become less sensitive to price levels. If the reverse of this were considered, it would lead to the conclusion that more information increases price elasticity. In this case, information indicates price information and the provision of information or the reduction of search costs represents a convenient way of comparing price information across products, vendors, and so on. Because the emergence of online platforms substantially enhanced the ability to compare prices, price elasticity may be higher for online demand than offline demand (Alba et al. 1997; Smith et al. 2001).

Compared with the explanations of classical economics, Bakos (1997) focuses on the role of individual preference, or fit, on the effect of reducing search costs for *product* information online. Fit cost occurs in differentiated markets where consumers have their ideal products and have to pay fit costs when they are not able to buy them and instead have to compromise and purchase others that fit less. The provision of product information clarifies quality and allows consumers to know whether the product is fitted or not. Thus, each buyer becomes captive to the seller who offers the best fit, which reduces the incentive to search further and thus reduces price elasticity.

This phenomenon has been consistently observed in empirical studies (Degeratu et al. 2000; Granados et al. 2012; Lynch and Ariely 2000). Using wine as a representative of a differentiated product, Lynch et al. (2000) show that lowering search costs for quality information decreases price elasticity, whereas enhancing price comparison capabilities increases price elasticity. This effect is not product-specific. Degeratu et al. (2000) confirm that price elasticity is lower online than offline, controlling for online promotion effects, which were treated as strong signals for price discounts. It is also asserted that in the differentiated market of air travel, online product information actually lowers the price elasticity of demand (Granados et al. 2012). A similar conclusion on the effect of product information has also been reached in the marketing literature, suggesting that increases in non-price advertising lead to lower consumer price sensitivity (Kaul and Wittink 1995).

Along these lines, because the items sold by Groupon are local services that are highly customized and differentiated but often involve less-known brands, it can be predicted that the provision of product information would reduce the price elasticity of demand for Groupon deals, which leads to following hypothesis.

Hypothesis 2: The effect of product information provided online lowers price elasticity in differentiated product markets.

2.3 Impact of Product Information According to Product Category

According to the literature in section 2.2, the provision of product information leads to lower price elasticity, but this effect could differ across different products.

By definition, consumers cannot verify the validity of advertising or information claims for experience products (Nelson 1975). In this situation, the provision of product information may be of no use for consumers. However, because consumers can determine the quality of search products prior to purchase, it is possible for them to verify the provided information, which surely improves the capability to judge quality. Therefore, there is a greater chance that consumers seeking experience products may not find relevant quality information to their evaluation procedures relative to those who seek search products. In other words, the value of the product information of search products exceeds that of experience products and consumers will therefore tend to put a greater weight on more valuable information sources to maximize total information value (Anderson 1971) when they do research for search goods.

Product category	Before score		After score		$M_b > 4$	$M_a > 4$	S/E Classification
	Mean	SD	Mean	SD			
Books	5.23	1.34	6.05	0.92	6.02	14.51	Search
Hotels	4.74	1.18	5.86	0.97	4.15	12.63	Search
Performance	4.88	1.55	6.09	0.95	3.75	14.50	Search
Subscription (e.g. magazine)	4.60	1.29	5.37	1.22	3.07	7.40	Search
Café	4.49	1.49	5.84	1.02	2.16	11.79	Search
Food (e.g. delivery or take-away)	4.42	1.30	6.23	0.75	2.12	19.50	Search
Sports event	4.51	1.61	5.81	1.28	2.09	9.31	Search
Dessert	4.37	1.23	6.12	0.82	1.98	16.87	Search
Restaurant (indoor)	4.37	1.29	6.07	0.86	1.89	15.85	Search
Photo (e.g. printing)	4.30	1.06	5.58	1.05	1.87	9.86	Search
Admission ticket (e.g. museum)	4.37	1.45	5.79	0.97	1.69	12.17	Search
Other goods	4.17	1.09	5.52	0.91	1.00	11.03	Experience
Household items	4.12	1.18	5.35	0.97	0.65	9.09	Experience
Apparel	4.14	1.44	5.88	0.82	0.64	15.02	Experience
Pub	4.12	1.33	5.60	1.16	0.57	9.09	Experience
Tour	4.07	1.42	5.65	1.11	0.32	9.75	Experience
Furniture	3.81	1.20	5.23	1.13	-1.02	7.15	Experience
Car service (e.g. car wash, repairs)	3.58	1.35	4.93	1.16	-2.03	5.25	Experience
Event	3.56	1.42	5.60	1.05	-2.04	9.98	Experience
Wine	3.47	1.26	5.07	1.47	-2.78	4.77	Experience
Activity	3.35	1.43	5.56	1.08	-2.99	9.50	Experience
Fitness	3.35	1.41	5.28	1.08	-3.02	7.79	Experience
Laundry (e.g. dry cleaning)	3.31	1.28	4.98	1.42	-3.53	4.50	Experience
Spa and massage	3.16	1.09	4.93	1.33	-5.04	4.57	Experience
Dental care	3.00	1.29	4.53	1.44	-5.08	2.44	Experience
Yoga	2.81	1.37	4.88	1.28	-5.69	4.53	Experience
Other lessons	2.77	1.29	5.14	1.06	-6.28	7.05	Experience
Beauty (e.g. hair)	2.79	1.25	5.79	1.12	-6.37	10.44	Experience
Sports lessons	2.77	1.17	5.09	1.17	-6.90	6.12	Experience
House services (e.g. cleaning)	2.84	1.09	5.09	1.19	-7.00	6.02	Experience
Beauty clinic (e.g. tanning, waxing, etc.)	2.79	1.12	4.98	1.34	-7.05	4.79	Experience
Facial treatment	2.79	1.06	4.53	1.50	-7.49	2.34	Experience

Table 1. Product categorization for search and experience products

It is therefore conjectured that the impact of the provision of product information on price elasticity can differ between search and experience goods, as follows.

Hypothesis 3: The effect of the product information provided in electronic markets on price elasticity is higher for search products than for experience products.

3 EMPIRICAL ANALYSIS

3.1 Product Categorization

Iacobucci (1992) has empirically explored goods and services according to the search-experience categorization, but the sample used in his work is quite different from that employed in this study. For our research, we conducted a pre-test in order to determine whether consumers perceive differences in the search and experience characteristics of services in the ways suggested in the literature (Darby and Karni 1973; Hsieh et al. 2005; Huang et al. 2009; Krishnan and Hartline 2001). Forty-three business school students were asked to participate in a survey. First, the participants were supplied with a short explanation of purchase decisions, which described how some services can be easily evaluated before purchase, whereas others cannot be evaluated even after use. The participants were then asked to evaluate how well they were able to judge the quality of a service before purchase on a seven-point scale ranging from 1 = “Not at all” to 7 = “Very well.” After using each service, participants were again asked to score their ability to evaluate the performance of the service using the same seven-point scale. The number of services employed in the survey was 32, meaning that participants had to answer a total of 64 questions, excluding some questions related to demographic information.

As in the literature, products that received high scores in both surveys were regarded as search-dominant products because their performance could be evaluated before and after purchase. Products that received low scores in the initial survey but high scores in the second survey were classified as experience-dominant products, indicating that consumers only had the ability to evaluate their quality after using them. In order to statistically distinguish between the search and experience categories at the 5% significance level (t=1.684), the midpoint of 4 was employed to determine whether scores were low or high. Table 1 shows the results of the classification based on a t-test, in which each mean score was statistically compared with the midpoint of 4. The results show that among the 32 goods and services, 11 were search-dominant and 21 were experience-dominant. Most goods and services provided by Groupon are experience goods and services that involve high quality uncertainty. The validity of the pre-test was established based on the fact that the respondents did not identify any service as being easy to evaluate prior to purchase but difficult to evaluate after use (Krishnan and Hartline 2001).

3.2 Data Description

To analyze the hypotheses, data was obtained by crawling the Groupon site (www.groupon.com) with an automated crawler specifically designed for Groupon. As in Figure 1, a typical Groupon deal includes information on the deal page such as the name of the product, its price, the number of items sold so far, the time left until the deal closes, and some brief information about the product. This data include sales of daily deals at the end of each deal across 52 cities in the United States and Canada from November 2 to December 9, 2010. The data set also contains a number of other unique attributes for each daily deal. The variables and their summary statistics are presented in Tables 2 and 3, respectively.

Unlike the typical sales data employed in empirical research, which contain only one or few types of products, these data include a variety of product types, thus enabling us to operationalize the concept of search and experience products, or the level of quality uncertainty. Thus, it becomes possible to observe moderating impacts on price elasticity based on the difficulty of evaluating quality.

Figure 1. A typical Groupon deal

Variable	Description
Sales	Number of items sold for each deal
Price	Price of a product
Tipp	Threshold for a deal to be on
FBL	Number of "Facebook Likes" for each deal
Online	Dummy variable for online versus offline
Experience	Dummy variable for experience versus search product
City	Dummy variable for each city
Day of week	Dummy variable for day of week

Table 2. Description of model variables

	Pooled(N=1363)				Search (N=598)		Experience(N=765)		Offline(N=1007)		Online(N=356)	
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Sales	603.37	1276.02	0	17473	587.99	899.08	615.38	1506.87	614.63	1138.43	571.49	1603.99
Price	29.68	29.69	3	200	19.82	18.99	37.38	33.98	31.85	32.93	23.53	16.10
Tipp	43.85	69.60	1	1000	47.07	72.42	41.34	67.26	47.70	75.91	32.98	45.79
FBL	29.93	81.94	0	2000	26.94	47.16	32.27	101.09	30.37	79.26	28.69	89.21

Table 3. Summary statistics for key variables

The measurement of price elasticity requires two key variables. One is the demand of a product, *Sales* in this data set, which indicates the number of items sold in a deal at a given *Price* level. As in Figure 1, every deal page provides a clear sales number. Another key variable is *Price*. Because Groupon covers a wide range of product categories, the prices are also varied, ranging from $3 to $200.

In order to measure the difficulty of evaluating quality, a dummy variable for experience goods and services is created (*Experience*), which imposes search goods and services as a base. This categorization is based on the results of the previously mentioned pre-test. Specifically, the value of Experience is 1 if a product is categorized as an experience good and 0 if it is categorized as a search good.

In addition, one more dummy variable is used to indicate the existence of online product information (*Online*). For some of the products, their website address appears on the title of the deal such that consumers are able to access additional product information that vendors want to show. Since most deals on Groupon involve non-national-brand local services, such as a small bistro in a local town, they often do not have websites. Thus, compared with those that have websites that provide product information *online*, the search costs of gathering product information would be much higher for *offline* deals. In this sense, the value of *Online* is 1 if a deal has its own website that can provide product information so that consumers can easily access and use this information in their evaluation procedures, and 0 otherwise.

There are other control variables related to the unique characteristics of Groupon deals that may impact Sales. First, a tipping point of each deal (*Tipp*) plays a role in the threshold of sales that needs to be reached for a deal to be on. If this threshold is not reached within a time limit (usually one day), the deal is off and every transaction already made is cancelled. In this case, no one can buy the product. As a result, the tipping point is carefully determined by vendors and Groupon advisors, because calling a deal off is not a desired outcome for either of them because neither can earn profits in this situation. Some features of deals could affect the level that this tipping point is set to, such as total capacity, but among these, the confidence of vendors regarding their attractiveness to potential Groupon consumers may lead to variations in established tipping points. The tipping point is set high when promoting relatively famous and large vendors that may provide good quality products. Otherwise, relatively non-famous and small vendors are likely to set low tipping points because they do not want to risk the deal being called off. In addition, because the tipping point is the minimum amount of sales for deals that are on, it represents a kind of rescaling of the initial point of sales. Given deals that are on, every deal has a guaranteed amount of sales, or tipping point, which is not related to other characteristics of the deal. For this reason, *Tipp* must be controlled for in this case.

Second, Groupon has substantially used functions of Social Network Services (SNS) to leverage the network effects of social networks. One example is *Facebook Likes* on deal pages. The number of Facebook Likes (*FBL*) indicates the participation of users who are interested in topics or items to which the like button has been attached. Facebook Likes represent the aggregated preferences of users for topics or items, as collected through SNS. They serve as endorsements from other consumers, revealing the preferences of consumers with regard to a product, which are influential in predicting demand in social commerce sites, where it is difficult for consumers to obtain quality information (Lee and Lee 2012). Additionally, because it could be suspected that *Sales* and *FBL* have a non-linear relationship, the square term of *FBL* (*sqFBL*) is included in the estimation models in order to capture this effect.

Moreover, we control for various consumer purchasing patterns through the day of the week the purchase is made (*Day of week*) and the differences in demand (or purchasing power) across cities (*City*).

3.3 Empirical Model Specifications

We develop estimation models to predict the sales of items on Groupon using a Cobb-Douglas demand function: $f(p,\mathbf{x}) = Ap^{\eta}\mathbf{x}^{k}$, where p is the price of the product and **x** is a vector of control variables. This multiplicative form of the equation can be transformed into a linear equation by taking the log of both sides: $\ln f(p,\mathbf{x}) = \ln A + \eta \ln p + k \ln \mathbf{x}$. Price elasticity is the percentage change in quantity associated with a percentage change in price. Using this relationship, price elasticity can be simply revealed by the coefficient of lnP, η, with a negative sign. The resulting estimation equation is developed as follows:

$$\ln Sales_i = \eta \ln Price_i + \ln \mathbf{X}\beta + \varepsilon_i \qquad (1)$$

X includes Tipp, FBL, sqFBL, and the other control variables mentioned above. With separate regressions for the two categories, equation (1) is used to indicate differences in price elasticity between search and experience products. As predicted by Hypothesis 1, it is expected that η in search goods is lower (price elasticity is higher) than it is in experience goods.

In addition to the basic model, it is necessary to build up equations to capture the interaction effect of the difficulty of evaluating quality (Experience) and the provision of online product information (Online).

$$\ln Sales_i = \eta \ln Price_i + \lambda_E Experience_i \cdot \ln Price_i + \sigma_E Experience_i + \ln \mathbf{X}\beta + \varepsilon_i \qquad (2)$$

$$\ln Sales_i = \eta \ln Price_i + \lambda_O Online_i \cdot \ln Price_i + \sigma_O Online_i + \ln \mathbf{X}\beta + \varepsilon_i \qquad (3)$$

In equation (2), Experience is a dummy variable representing experience products and the interaction effect is considered by including a product term between Experience and the log of price. Most studies suggest that when considering the interaction effect by adding a product term, a component term of this product term must be included in the model to avoid misinterpretation of the results (Brambor et al. 2006). A positive estimate of λ_E will support that price elasticity is higher for search products than experience goods.

Similarly, equation (3) measures the interaction effect of online product information on price elasticity. Hypothesis 2, which states that in differentiated product markets, the provision of product information lowers price elasticity, is confirmed by a positive λ_O. Also, separate regressions by Experience are conducted with equation (3) to test if the effect of product information is higher in search products than experience products, which can be verified by comparing λ_O in each regression.

3.4 Regression Diagnostics

In using multivariate regression models, it is important to consider multicollinearity among the employed variables. The consequence of this problem is inefficiency in standard errors, causing a larger standard deviation of coefficients (Greene 2008). Even if the estimated coefficients are unbiased, it is still a good idea to check for this problem.

The variance inflation factor (VIF) given in Table 4 is the most widely used indicator for checking for multicollinearity problems. A VIF above 10 implies that the potential for multicollinearity might cause problems. The table shows no variable exceeding a VIF of 10, so it can be concluded that the models used in the study are free from this problem. Correlations and VIF values for the fixed effect dummies (Day of week and City) are excluded in the table for brevity. The highest VIF among all variables was 2.55, for a dummy for Dallas. It can thus be concluded that this model is free from multicollinearity concerns.

Variable	Price	Tipp	FBL	Online	Experience	VIF
Sales						
Price	1					1.11
Tipp	0.0047	1				1.12
FBL	-0.0336	0.3112	1			1.11
Online	-0.1231	-0.093	-0.009	1		1.02
Experience	0.2937	-0.0408	0.0323	-0.0263	1	1.1
note: Correlations for Day of week and City dummies excluded for brevity; the highest VIF among the fixed effect dummies was 2.55 for a dummy for Dallas.						

Table 4. Correlations of model variables

The classic ordinary least squares regression model assumes homogenous disturbances. From the result of the Breusch-Pagan test, however, it is confirmed that the disturbance is not homogenous ($\chi^2(1) = 35.42$). Because this problem can invalidate statistical tests of significance, Hurber-White heteroscedasticity-consistent standard errors are used to measure correct standard errors instead of regular ones.

4 RESULTS

Table 5 presents the result of testing hypothesis 1, which states that price elasticity is higher for search products than experience products. In pooled regressions, the interaction term between lnPrice and Experience has a positive and significant coefficient, supporting hypothesis 1. At first, only interaction term is added in the model and its coefficient support the hypothesis at 5% significance level. To be sure about the direction of interaction term, in second column the component term (Experience) is added in the model. The interaction effect is still observed, but with lower significance level (10%) due to the component term. Sub-sample analyses also assist in reaching this conclusion by showing that the price elasticity of demand is 0.478 (η=-0.478) for search products, whereas it is 0.356 (η=-0.356) for experience products.

	Pooled	**Pooled(with dummy)**	**Search product**	**Experience product**
lnPrice	-0.419***	-0.463***	-0.478***	-0.356***
	(-9.936)	(-8.437)	(-8.260)	(-7.434)
Experience*lnPrice	0.038**	0.121*		
	(2.161)	(1.748)		
Experience		-0.266		
		(-1.284)		
lnTipp	0.343***	0.345***	0.330***	0.337***
	(7.384)	(7.397)	(4.745)	(5.235)
lnFBL	-0.145***	-0.149***	-0.071	-0.209***
	(-2.647)	(-2.723)	(-0.818)	(-3.139)
sqlnFBL	0.106***	0.107***	0.106***	0.108***
	(10.477)	(10.561)	(6.720)	(8.828)
constant	5.247***	4.984***	4.975***	4.816***
	(14.436)	(20.092)	(14.422)	(14.588)
Day of week dummy	(Included)	(Included)	(Included)	(Included)
City dummy	(Included)	(Included)	(Included)	(Included)
Number of observations	1,363	1,363	598	765
Adjusted R2	0.690	0.691	0.689	0.694
note: Huber-White heteroscedasticity-consistent t-values are in the parentheses; *** p<0.01, ** p<0.05, * p<0.1				

Table 5. Price elasticity of search and experience products

In addition to the main effect, Tipp also exhibits the expected significant relationships with the dependent variable. Tipp has a positive and significant coefficient, confirming the role of the tipping point in increasing sales.

In contrast, lnFBL exhibits the opposite sign than previously expected. It has negative and significant sign (-0.149), indicating that as the number of Facebook Likes increases, sales decrease. This can be justified, however, by interpreting the joint effect with the square term of lnFBL. A positive sign of the square term indicates a U-shaped relationship between lnFBL and lnSales. The question is at which level of FBL the slope goes up. In a pooled model in Table 4, taking a partial derivative of lnFBL gives 0.696 for the amount of FBL at which point the slope becomes positive. By taking log off, it can be stated that the relationship between FBL and Sales becomes positive when FBL is above 2, which is a fairly low level for these data, in which the mean of FBL is 29.93. It may thus be more appropriate to describe the negative coefficient as a temporary effect restricted to very low levels of FBL. This means that within the feasible range of the data, Facebook Likes positively influence sales.

In Table 6, the impact of online product information on the price elasticity of demand is measured in differentiated markets, which are covered by hypothesis 2. The results of a pooled regression and separated regressions all indicate that the provision of product information online lowers price elasticity in differentiated markets in which there are individual preferences and fit costs in which utility is lost by purchasing non-ideal products (Bakos 1997).

	Pooled	**Offline**	**Online**
lnPrice	-0.414***	-0.407***	-0.218**
	(-12.532)	(-11.660)	(-2.104)
Online*lnPrice	0.296***		
	(2.975)		
Online	-1.208***		
	(-4.019)		
lnTipp	0.305***	0.330***	0.231**
	(6.612)	(6.040)	(2.171)
lnFBL	-0.184***	-0.250***	-0.060
	(-3.325)	(-3.502)	(-0.721)
sqlnFBL	0.111***	0.113***	0.112***
	(10.629)	(8.335)	(7.555)
constant	5.123***	5.140***	4.211***
	(21.466)	(18.569)	(8.165)
Day of week dummy	(Included)	(Included)	(Included)
City dummy	(Included)	(Included)	(Included)
Number of observations	1,363	1,007	356
Adjusted R2	0.698	0.677	0.732
note: Huber-White heteroscedasticity-consistent t-values are in the parentheses; *** p<0.01, ** p<0.05, * p<0.1			

Table 6. Impact of online product information on price elasticity

Hypothesis 3 considers the varying effect of online product information conditioned by the degree of difficulty of evaluating product quality. To test this, separate regressions for search and experience products are conducted with a model including an interaction term between Online and lnPrice. In Table 7, as expected by hypothesis 2, the interaction term in both models has a positive coefficient, but it is significant only for search products. In addition, the size of the coefficient is also larger for search products than experience products, which implies that the effect of product information in search products outweighs that of experience products. The price elasticity of search products for which online product information is provided is -0.141(-0.484+0.343), which is also lower than that of experience products, -0.214(-0.388+0.174). This leads to the acceptance of hypothesis 3.

	Search product	**Experience product**
lnPrice	-0.484***	-0.388***
	(-7.705)	(-7.439)
Online*lnPrice	0.343**	0.174
	(2.308)	(1.216)
Online	-1.571***	-0.634
	(-3.596)	(-1.414)
lnTipp	0.227***	0.337***
	(3.268)	(5.235)
lnFBL	-0.159*	-0.210***
	(-1.875)	(-3.077)
sqlnFBL	0.113***	0.107***
	(7.397)	(8.453)
Constant	5.526***	4.941***
	(15.026)	(14.467)
Day of week dummy	(Included)	(Included)
City dummy	(Included)	(Included)
Number of observations	598	765
Adjusted R2	0.711	0.694
note: Huber-White heteroscedasticity-consistent t-values are in the parentheses; *** p<0.01, ** p<0.05, * p<0.1		

Table 7. Impact of online product information by search and experience products

5 DISCUSSION AND CONCLUSION

This research investigated how price elasticity differs according to the degree of difficulty of evaluating product quality by distinguishing between search and experience products, those for which product information is provided, and their combination. To explore this, it used 1,363 samples of Groupon sales data obtained by crawling the Groupon website from November 2, 2010 to December 9, 2010. An additional pretest was conducted to classify products according to the degree of difficulty involved in evaluating their quality in order to identify products as search or experience products.

All three hypotheses are supported through the empirical analysis. First, we can conclude that price elasticity is higher for search products than experience products. Second, it is confirmed that online product information decreases price elasticity in differentiated product markets as the results of the literature that has consistently supported this argument. While previous studies rather lie on a few categories, a wide range of differentiated products is considered in this study, which shows the generality of the argument. The results also indicate that this effect varies according to difficulty. The coefficient of the interaction term between Online and lnPrice is higher for search products than experience products. For experience products, the coefficient is insignificant, which implies that for consumers, information value to the estimation procedure can differ according to what type of product they are dealing with.

This paper contributes to the literature in three ways. First, although the issue of price elasticity in electronics markets has been widely examined, there has been little empirical evidence to deal with it. This is because of the availability of sales and price data on the Internet (Granados et al. 2012). In this study, these two important types of variables which are sales and prices are apparently provided by Groupon so that price elasticity can be explicitly measured. The second contribution is related to another virtue of the data, which represent a wide range of product categories, thus enabling us to operationalize the degree of difficulty of the evaluation of quality according to Nelson's categorization of goods. Previous studies have focused on only one or a few types of products because of the availability of data (e.g. Granados et al. 2012; Lynch and Ariely 2000). Thus it was not possible to reflect results associated with the diversity of product categories and hard to generalize the observed patterns. Out data set contains 32 types of goods and services and would be sufficient to secure the generalizability of the results found in this research. Finally, this study demonstrates the effect of difficulty on the price elasticity of demand. To the best of our knowledge, this is one of the first studies to consider consumer difficulty in evaluating quality and linking it with information provision in electronics markets. The difficulty to evaluate product quality does have significant effects on consumer behavior in that the basic assumption that consumers can judge the quality and interpret signals about the product from sellers is no longer valid. In this line, it seems plausible to conjecture that the way in which consumers obtain required information to evaluate quality based on the difficulty, or the search cost, can induce changes in how consumers respond to information in the evaluation processes. Despite of all, this has not been widely considered in the literature due to the availability of such data. This study taking the difficulty into consideration helps to better understand how consumers respond to product information and the conditional dependence of this effect on how they interpret such information.

Even though substantial efforts have been devoted to make the research flawless, there are some limitations. First concern is with the data set. It has been two years since the data was gathered, which was Nov. 2010. Although there have been no major change in business models and structured in the website, it is still worth to concern the dynamic change of the perception on Groupon, or social commerce industry. Compared with 2010 when Groupon and other social commerce sites flourished and experienced great success in the market, now is a different era in which the growth rate is rapidly dropped and a lot of firms have been forced to close the business because of harsh competitions. Social commerce, on the other hand, now has become ordinary shopping behavior. Most of consumers are familiar with the concept of social commerce and more frequently use these sites than the past. These transitions might have impact on consumer behavior in Groupon which in turn influences the results of this research. Yet, it is still plausible to believe that there would be no substantial impacts on the results because the structure and functions adopted in the website is still remained same. Our results are dependent on what influences purchase decisions at the time consumers are making the decision, thus in this sense the time gap would not harm the essence of the results and implications.

Along with the concern of the data set above, the fact that only Groupon was employed in this research may be considered as an issue to concern. With lack of generalizability Groupon data set might cause, the potential to expend the results and the implications of this research to more general sense would be limited. Possessing extensive market power, Groupon, however, is the largest social commerce site in U.S. in both that time when the data was collected and nowadays and thus it is plausible to tell that it is a representative of the social commerce market. Furthermore, considering the fact that other sites have been shrank makes the above assumption more believable and mitigates the concern about generalizability.

Third, there is an issue associated with the categorization. While search/experience categorization in goods has been widely adopted and constructed with solid methods, search/experience services have had less attention in literature. Service itself has some experience characteristics so that it is hard to neatly divide it into two categories. In fact, according to the definition of search goods that the quality can be evaluated before using it, the quality of all services is not easy to tell prior to actually using it. Thus, the classification scheme used for goods might not be applicable to services. Despite of this, the literature dealing with services has used similar methods to categorize services into search and experience services (Iacobucci 1992; Iacobucci and Ostrom 1996; Mitra et al. 1999; Ostrom and Iacobucci 1995), it seems to plausible to adopt the scheme in this research too.

Despite of the limitations, this research provides interesting implications to practices of online businesses. Our results confirmed that the provision of product information may have a very limited effect on elasticity for experience products whereas it decreases elasticity for search products. This is because product attributes related to the quality of experience products cannot be ascertained by prior search (Nelson 1970; Nelson 1974). This finding suggests an important implication for online businesses with regard to information provision. Many online retailers have provided product information in order to lock-in their customers by revealing their fit costs (Bakos 1997). They often provide information, however, without considering consumer difficulty in evaluating this information. The use of multimedia tools or interactive channels in the electronics markets might help to provide differentiated product information; however, just providing a simple and derivative introduction about a product on a webpage would not enhance the consumer's capability to evaluate its quality. The provided information should be customized to the nature of the product in terms of the consumer's information search procedure to obtain what online retailers aim to achieve in the first place: locking-in their customers and increasing their profitability. Otherwise, they could not capture profits and would just waste money building IS infrastructure to provide such online services. Therefore, firms must provide relevant information for each category to make sure that consumers can determine which product best fits their preferences so that they become captive to the sellers.

References

Alba, J., Lynch, J., Barton, W., Janiszewski, C., Lutz, R., Sawyer, A., and Wood, S. (1997). Interactive Home Shopping: Consumer, Retailer, and Manufacturer Incentives to Participate in Electronic Marketplaces, Journal of Marketing, 61(3), 38-53.

Anderson, N. H. (1971). Integration theory and attitude change, Psychological Review, 78(3), 171-206.

Bakos, J. Y. (1997). Reducing buyer search costs: Implications for electronic marketplaces, Management science, 43(12), 1676-1692.

Brambor, T., Clark, W. R., and Golder, M. (2006). Understanding interaction models: Improving empirical analyses, Political analysis, 14(1), 63-82.

Chang, T. Z., and Wildt, A. R. (1994). Price, Product Information, and Purchase Intention: An Empirical Study, Journal of the Academy of Marketing Science, 22(1), 16-27.

Darby, M. R., and Karni, E. (1973). Free Competition and the Optimal Amount of Fraud, Journal of Law and Economics, 16(1) 04/01, 67-88.

Degeratu, A. M., Rangaswamy, A., and Wu, J. (2000). Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes, International Journal of Research in Marketing, 17(1), 55-78.

Dodds, W. B., Monroe, K. B., and Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations, Journal of Marketing Research, 28(3), 307-319.

Gardner, D. M. (1971). Is there a generalized price-quality relationship?, Journal of Marketing Research, 8(2), 241-243.

Granados, N., Gupta, A., and Kauffman, R. J. (2012). Online and Offline Demand and Price Elasticities: Evidence from the Air Travel Industry, Information Systems Research, 23(1), 164-181.

Greene, W. H. (2008). Econometric Analysis, 6th ed. Prentice-Hall: NJ.

Hsieh, Y. C., Chiu, H. C., and Chiang, M. Y. (2005). Maintaining a committed online customer: A study across search-experience-credence products, Journal of Retailing, 81(1), 75-82.

Huang, P., Lurie, N. H., and Mitra, S. (2009). Searching for experience on the web: An empirical examination of consumer behavior for search and experience goods, Journal of Marketing, 73(2), 55-69.
Iacobucci, D. (1992). An empirical examination of some basic tenets in services: goods-services continua, Advances in services marketing and management, 1, 23-52.
Iacobucci, D., and Ostrom, A. (1996). Perceptions of services, Journal of Retailing and Consumer Services, 3(4), 195-212.
Kaul, A., and Wittink, D. R. (1995). Empirical Generalizations About the Impact of Advertising on Price Sensitivity and Price, Marketing Science, 14(3 supplement) June 20, 1995, G151-G160.
Krishnan, B., and Hartline, M. (2001). Brand equity: is it more important in services?, Journal of Services Marketing, 15(5), 328-342.
Lee, K., and Lee, B. (2012). When Does the Recommendation of Other People Matter in Social Commerce Even Though They Have Not Purchased Either?, ICIS 2012 Proceedings.
Lynch, J. G., and Ariely, D. (2000). Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution, Marketing Science, 19(1) Winter 2000, 83-103.
Mitra, K., Reiss, M. C., and Capella, L. M. (1999). An examination of perceived risk, information search and behavioral intentions in search, experience and credence services, Journal of Services Marketing, 13(3), 208-228.
Monroe, K. B. (1973). Buyers' Subjective Perceptions of Price, Journal of Marketing Research, 10(1), 70-80.
Nelson, P. (1970). Information and Consumer Behavior, Journal of Political Economy, 78(2), 311-329.
Nelson, P. (1974). Advertising as information, The Journal of Political Economy, 82(4), 729-754.
Nelson, P. (1975). The Economic Consequences of Advertising, The Journal of Business, 48(2), 213-241.
Olson, J. C. (1976). Price as an informational cue: Effects on product evaluations, College of Business Administration, Pennsylvania State University.
Ostrom, A., and Iacobucci, D. (1995). Consumer Trade-Offs and the Evaluation of Services, Journal of Marketing, 59(1), 17-28.
Rao, A. R., and Monroe, K. B. (1988). The Moderating Effect of Prior Knowledge on Cue Utilization in Product Evaluations, Journal of Consumer Research, 15(2), 253-264.
Rao, A. R., and Monroe, K. B. (1989). The Effect of Price, Brand Name, and Store Name on Buyers' Perceptions of Product Quality: An Integrative Review, Journal of Marketing Research, 26(3), 351-357.
Smith, M., Bailey, J., and Brynjolfsson, E. 2001. "Understanding digital markets: Review and assesment," Working paper, SSRN (http://ssrn.com/abstract=290326).
Wolinsky, A. (1983). Prices as Signals of Product Quality, The Review of Economic Studies, 50(4), 647-658.